

Modeling community structure and topics in dynamic text networks

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Abstract

The last decade has seen great progress in both dynamic network modeling and topic modeling. This paper draws upon both areas to create a Bayesian method that allows topic discovery to inform the latent network model and the network structure to facilitate topic identification. We apply this method to the 467 top political blogs of 2012. Our results find complex community structure within this set of blogs, where community membership depends strongly upon the set of topics in which the blogger is interested.

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1 Introduction

Dynamic text networks have been widely studied in recent years, primarily stemming from the Internet’s ability to store textual data in a way that allows links between different documents. Articles on the Wikipedia [1], citation networks in journal articles [2], and linked blog posts [3] are all examples of dynamic text networks. The analysis of this type of data requires methodology that combines dynamic network models with dynamic topic models. In this article we develop a novel Bayesian approach for modeling the interaction between textual data and network structure. We apply this model to the blog posts of the top 467 US political blogs in 2012.

The last decade has seen progress in both topic modeling and network modeling separately. There are models that allow change in the topic structure of a corpus of text data [4]. Similarly, statistical models for dynamic networks has grown much more sophisticated [5, 6, 7]. Evolving exponential random graph models [8] and stochastic actor based models [9] provide powerful tools for investigating dynamic network structure.

Researchers have started to develop models that combine network analysis and topic analysis, mostly in the context of static networks. [10] describes a relational topic model in which the probability of links between documents depends upon their topics, and applies it to two datasets of abstracts and a set of webpages from computer science departments. [11] applies such methods to linked hypertext and citation networks. [12] develops a model for the case in which there are noisy links between nodes, in the sense that there are links between documents whose topics are not related. [13] does related work on clustering documents through use of a topic model.

A standard challenge in analyzing network data is to uncover community structure, or groups of nodes that are more interconnected with each other than they are connected with other nodes in the network. One of the common models for such groups is the stochastic block model [14]. The stochastic block model places nodes into latent communities based on the observed pattern of links between nodes. Another method for assessing community structure is the latent space model [15], which places each node in a multidimensional unobserved “social space” that explains the observed link structure.

While the above methods work well for the classification of nodes into communities when one only has a network as input data, for the analysis of dynamic text networks, the goal is to discover latent communities of nodes using information from both the text generated by at the nodes and the links between nodes. To our knowledge, there is no previous community detection methodology that jointly models both the text dynamics and the network structure.

In this study we develop a Bayesian model for estimating both the latent community structure in a dynamic network of text generating nodes, where the text being generated by these nodes has dynamic topic structure as well as the latent dynamic topic structure. The model that we develop fulfills three requirements, all of which are motivated by the application to the network of 2012 political blog posts.

First, the dynamic topic model must allow for the sudden and unpredictable appearance of new words in a topic. Previous dynamic topic models describe the change in topic by an AR(1) process [4], which allows for slow drift of the probability that a word appears. However, changing topic structure in many real world data sets is likely to be fast and unpredictable, particularly regarding the inclusion of new terms. For example, in 2012 the word “Benghazi” was absent from blog and news coverage before September 11, but afterwards had relatively high probability. For blog discussion of news events, realistic models must allow more rapid vocabulary change than standard time series methods permit.

The second requirement is that the network model must classify nodes into blocks, so that nodes within the same block are more likely to form links, while nodes from different block-pairs have

lower probabilities of linking. This reflects the observed fact that many bloggers tend to interact mostly within small groups that share common interests, but sometimes a blogger will link to a post outside his group. Identification of block structure corresponds to community detection.

The third requirement is that the network model allows use of covariate information. Complex and dynamic networks cannot be wholly described in terms of simple block structures. In the context of political blogs, one also must account for such factors as the prestige of the blog, the occurrence of newsworthy events, and other explanatory variables. This extends the use of covariates from static stochastic block models, as in [16] to dynamic networks. Notably, some covariates may be fixed (e.g., prestige) whereas others are time-varying (e.g., time since last newsworthy event).

The Bayesian model used in this research satisfies these three requirements by integrating a stochastic blockmodel with an novel extension of Dirichlet mixture modeling for short text analysis [13] for topic discovery. We use this model to analyze the network of interactions among the top 467 U.S. political blogs from 2012 across the entire year. The analysis reveals a distinct set of dynamic topics that jointly define a latent community structure.

2 The Model

The model assumes that each blogger generates a variable number of posts at each (discrete) time point (i.e., each day). Each post is about a single topic where a topic is a probability distribution over the vocabulary; for example, if the high probability words are “Trayvon”, “Aurora” and “Sandy Hook”, then one might infer that the topic is crime.

A blogger might post primarily on a single topic, which, from our reading of the data, is generally the case. However, a blogger may post about different topics at different times. The collection of topics that interest a specific blogger are fixed across the year (e.g., a blogger might post solely about two topics, say the U.S. presidential campaign and the Middle East), but the content in those topics can change (e.g., Newt Gingrich fades out of the presidential race, so “Gingrich” diminishes slowly, or Herman Cain enters the race, in which case his name suddenly appears with relatively high probability).

The number of daily posts on a specific topic is a random variable. When the topic is in the news, we say that the topic is active and the probability that a blogger posts about it is elevated. This reflects observed structure in the data; e.g., after the Aurora shooting by John Holmes, there was a relatively high rate of posting on the topic of crime, but a few weeks later the rate of posting on this topic dropped back to its baseline.

Additionally, each blogger is assumed to belong to a block. People within the same block are interested in the same collection of topics, but possibly to different degrees. Bloggers within the same block are more likely to link. Less likely to link are bloggers in different blocks but who are interested in the same topic, and even less likely are bloggers that are not interested in the same topic.

Each blog post is a single observation, with day of post, blogger posting, blogs linked to, and the vocabulary of the post making up the data for each observation. For each day, the blogs linked to are aggregated into a single binary directed network of which blogs linked to which other blogs that day. For 2012, one observes a time series of 366 networks, along with the text of each post at each of the 467 blog sites. The notation for this model is as follows:

- time is indexed by t , for $t = 1, \dots, T$ with $T = 366$;
- the node set is \mathcal{N} , with n being the total number of nodes in the network;

- the directed network of blogs linking to other blogs at time t is represented by the $n \times n$ adjacency matrix A_t ;
- the set of all blog posts is \mathcal{D} , and D_{it} is the set of posts made by node i on day t ;
- a specific post is denoted by d_{ijt} , the j th post on the i th node at time t —each d_{ijt} is a $1 \times |V|$ vector of token counts, where $|V|$ is the total size of the vocabulary;
- the total number of topics is K ;
- the $K \times |V|$ matrix V_t indicates the vocabulary distribution of each topic over each time point t ;
- the $K \times T$ matrix E of $\{0, 1\}$ indicators that show whether topic k is quiet or active at time t ;
- let B be the set of block memberships for \mathcal{N} (i.e., $B_i = \{1, 4, 6\}$ means that node i primarily posts on topics 1, 4 and 6); nodes with the same interests are in the same block.

For computational reasons, we chose to restrict nodes to have primary interest in only 1, 2, 3 or all K topics. This reflects the fact that most bloggers only discuss a few topics, but there are websites, such as *The Huffington Post*, that post on essentially all possible topics.

The generative model assumes that given the blogsite’s membership in block B_i , the site’s topic interest vector π_i is drawn from a Dirichlet distribution with the following parameters:

$$\alpha_k = \begin{cases} P, & \text{if } k \in B_i \\ 1, & \text{if } k \notin B_i \end{cases} \quad (1)$$

where $P > 1$ is a parameter that controls the concentration of the site’s interest on its block’s topics. Large values of P imply that the post is very likely to reflect the the interests of the block. Thus the model explicitly allows for nodes to generate text on topics outside of their block’s primary interests, but with generally low probability.

At time t the number of posts on topic k generated by blogsite i is drawn from a Poisson distribution with parameter

$$\lambda_{tki} = \rho_i \pi_{ik} + \rho_i E_{tk} \psi_k \quad (2)$$

where ρ_i is the average posting rate for blogsite i , π_{ik} is the interest level of blog i in topic k , E_{tk} is the activation indicator of topic k on day t , and ψ_k is the activation parameter for topic k . The first product indicates a baseline rate for how prolific the i th blog is for posting on the k th topic. The second product boosts the rate of posting when some event has occurred that is relevant to topic k , and the magnitude of the boost may vary by topic (e.g., we observe that sensational crime seems to be inherently more interesting than the presidential campaign). Summing these Poisson variables over k gives D_{it} , the total number of posts made by blog i at time t .

Given D_{it} , the next step is to generate each post. For the j th text object d_{ijt} , the number of words in the post is a draw from a Poisson with mean λ_D , and the content of the post is generated by i.i.d. draws from the multinomial distribution with parameter vector V_{kt} , where k is the topic assignment of d_{ijt} . The multinomial parameter vector changes over time, as new terms are introduced and the probabilities of older terms evolve (e.g., the frequency with which Newt Gingrich’s name appears in the corpus declines over 2012). There is a great deal of flexibility in modeling the dynamics of V_{kt} ; we assume that $V_{kt} = V_{k,t-\ell} + \mu_{k,t}$ where $\mu_{k,t}$ can be viewed as

an innovation matrix that determines how rapidly the k topic changes at time t and ℓ is a pre-specified lag parameter; in this paper, $\ell = 62$ (two months). This specification preserves temporal dependency in topics, while allowing sudden change in vocabulary.

In this dynamic text network, the network structure is generated using the exponential random graph model (ERGM) framework proposed by [17]. An ERGM describes the network adjacency matrix A with covariate vector x using a set of network statistics $s(A, x)$ where the probability of an observed network is:

$$P(A|\theta, x) = \frac{\exp(\langle \theta, s(A, x) \rangle)}{\sum_{A^* \in \mathcal{A}} \exp(\langle \theta, s(A^*, x) \rangle)} \quad (3)$$

where θ is the parameter vector, $s(\cdot, \cdot)$ is a function that maps an observed network and its covariate set onto a set of statistics, and $\langle \cdot, \cdot \rangle$ denotes the inner product operator.

The set of statistics $s(A, X)$ may contain both network statistics, such indegree and outdegree, and exogenous covariates, such as political affiliation. If the statistics include non-dyadic elements, such as triangle counts, then the normalizing constant in (3) sums over every possible network of a given size, which is extremely computationally intensive to estimate. As both the topic analysis and the stochastic block components of this model are also extremely computationally intensive, in this estimation procedure non-dyadic effects such as transitivity are approximated using the block structure imposed by the topic interest. As these block assignments are estimated conditional on the rest of the ERGM model, this simplifies the estimation of the ERGM parameters and allows the ERGM model to be expressed as the following conditional probability

$$\mathbb{P}[A_{ii'} = 1 | \theta, X, B_i, B_{i'}] = \frac{\exp(\langle \theta, s(A, X)_{ii'} \rangle)}{1 + \exp(\langle \theta, s(A, X)_{ii'} \rangle)} \quad (4)$$

where $A_{ii'}$ equals 1 if there is an edge between nodes i and i' and is otherwise 0.

In the blog application, both the adjacency matrix and the covariates may change over time, so we denote these by A_t and x_t , respectively, and $A_{ii't}$ indicates whether or not blog i has linked to blog i' at time t . The covariates used in this study are:

- the block memberships of blogs i and i' , since blogs within the same block are more likely to link, and blogs in different blocks that share interest in the same topic are somewhat more likely to link;
- an binary indicator $L_{i't}$ that takes the value 1 if the blog i' has linked to within the last week, and otherwise is 0.
- the average indegree over time of the receiving node, $I_{i'}$.
- the average outdegree over time of the sending node, O_i .

Specifically, the covariate describing block membership is

$$B(i, i') = \begin{cases} 1, & \text{if } B_i = B_{i'} \\ \langle \pi_i, \pi_{i'} \rangle, & \text{if } B_i \neq B_{i'} \end{cases}. \quad (5)$$

Recall that π_i is the vector that allocates the i th blog's interest among the K topics, and similarly for $\pi_{i'}$. Since the sums of each vector's components are 1, then the dot product cannot exceed 1.

Thus, the logistic regression for the network dynamics is

$$\ln \frac{\mathbb{P}[A_{ii't} = 1]}{1 - \mathbb{P}[A_{ii't} = 1]} = \theta_0 + \theta_1 B(i, i') + \theta_2 L_{i't} + \theta_3 I_{i'} + \theta_4 O_i. \quad (6)$$

Additional covariates could be added (e.g., to indicate whether the two blogs of the same political party, or whether the two blogs have ever linked in the past), but this simple model performs well.

The dynamics of the link network are captured in the block membership matrix and the lag indicator variable. The use of this ERGM model rather than a STERGM [8] or a stochastic actor oriented model (SAOM) [9] is warranted due to the structure of the link matrix. Rather than having a persistent set of edges that form or dissolve due to formation and dissolution processes, as they would be modeled in STERGM or SAOM methodology, the links in this data are day specific, and can be viewed as dissolving at the end of every day. The current ERGM model can be viewed as a day specific edge formation model that borrows block and popularity information from the entire time course, and accounts for the burst nature of linkages using the lag indicator variable $L_{i't}$.

The last component of the generative model is the activation matrix E . It is a $K \times T$ binary matrix, and if entry $E_{kt} = 1$, then the k th topic is in the news at time t . The current analysis assumes that the states on successive days are independent, so the time sequence for the k th topic is a set of Bernoulli draws with parameter η_k . An attractive alternative is to use a Hidden Markov Model [18] or a discretized version of the Markov modulated Poisson process [19]

3 Estimation

We use a Metropolis within Gibbs sampling algorithm [20] to obtain posterior distributions for the parameters defined in the generative model. This approach consists of four stages:

1. Assign each post d_{ijt} to a topic and update the matrix of vocabulary distributions V_t at each time step.
2. Update the blog parameters and the activation parameters, such as blogsite topic interest (π_{ik}), the base rate for posting (ρ_i), the E matrix, and activation level parameters (ψ_k).
3. Update the network parameters, i.e., θ_0 , θ_1 , θ_3 and θ_4 .
4. Update the blogsite's block membership.

The model requires that several parameters be specified *a priori*. The first and most important parameter is K , the total number of topics. In principle, one could place an informative prior on the number of topics and use the posterior mean determined by the data. But this is computationally cumbersome, and so we make the usual decision to specify the number of topics in advance, after some data exploration. This approach is used in [4] and [21]. One can use penalized likelihood as a selection criterion, as described in [13], or an entropy based criterion, such as the one described in [22]. We chose the number of topics by running models with different values of K and selecting the number of topics using the entropy based criterion in [22].

Additionally, the time lag for topic dependency lag ℓ needs to be specified. This time lag determines the scale of the topics. As we were interested in general topics of discussion among the political blogs we chose two months, or 62 days. For the node specific parameters, only P , the level of concentration on topics of interest to a block, is needed. We chose to set the concentration parameter equal to 50, ensuring that bloggers rarely post outside their areas of interest. Finally, for any reasonable number of topics, a restriction on the block structure is required to ensure computational feasibility. For an unrestricted block structure with K topics, the total number of possible blocks that must be evaluated is $\sum_{i=1}^K \binom{K}{i}$, which is intractable for moderate K . In this paper, we restrict blocks to have 1, 2, or 3 topics, or be the block that is interested in all topics.

3.1 Topic Modeling and Post Assignment

To infer the topics, we adapt the Gibbs Sampler for the Dirichlet Mixture Model (GSDMM) of [13]. As originally proposed, the GSDMM classifies a set of documents into specific topics. The topics are assumed to be generated by draws of a multinomial specific to each topic, and words (or tokens) may be shared across topics (e.g., common words such as “therefore”). This differs from the Latent Dirichlet Allocation model, which models documents as mixtures across a number of topics. GSDMM estimates the probability that a document d is about topic k , given the current topic vocabulary distribution, as

$$P(Z_d = k | V_k, d) = \frac{m_{k,-d} + \alpha}{|D| - 1 + K\alpha} \frac{\prod_{w \in d} \prod_{j=1}^{N_d^w} (N_{k,-d}^w + \beta + j - 1)}{\prod_{i=1}^{N_d} (n_{k,-d} + |V|\beta + i - 1)}, \quad (7)$$

where $m_{k,-d}$ is the number of documents currently assigned to topic k (not including the topic assignment of document d), N_d^w is the number of occurrences in document d of token w , and $N_{k,-d}^w$ is the number of occurrences of token w in topic k (not including the content of document d). The α controls the prior probability that a document is assigned to a topic; increasing α implies that all topics grow equally likely. The β relates to the prior probability that a token will have relevance to any specific topic; increasing β results in fewer topics being found by the sampler.

As originally proposed by [13], GSDMM is a static model. We modify it by allowing V to vary over time. For readability, we suppress the subscripts and denote the specific document d_{ijt} by d . Let $m_{k,t,-d}^* = \sum_{i=t-\ell}^t m_{ik}$ be the number of posts assigned to topic k in the interval from $t - \ell$ to t , not including post d by blog i at time t . And let

$$N_{k,t,-d}^{*w} = \sum_{i=t-\ell}^t N_{k,i}^w \quad (8)$$

be the number of of times that token w occurs in topic k in the interval from $t - \ell$ to t , not including document d . This defines a sliding window that allows the sampler to use information from the recent past to infer the topic to which a post belongs, while allowing new tokens to influence the assignment of the post at the current time point. The probability of assigning post d to topic k is then:

$$\mathbb{P}[Z_d = k | V_{kt}, d] = \frac{m_{k,t,-d}^* + \alpha}{|D| - 1 + K\alpha} \frac{\prod_{w \in d} \prod_{s=1}^{N_d^{*w}} (N_{k,t,-d}^{*w} + \beta + s - 1)}{\prod_{i=1}^{N_d} (N_{k,t,-d}^* + |V|\beta + i - 1)}. \quad (9)$$

Note that (9) does not use information about the blogsite that generates the post. So the final step is to incorporate the tendency of blogsite i to post on topic k at time t , using the Poisson parameter in (2). Using the normalized point-wise product of conditional probabilities, the final expression for the probability that post d (i.e., d_{ijt}) belongs to topic k is

$$\mathbb{P}[Z_d = k | V_{k,t}, d, \lambda_{ikt}] = \frac{\mathbb{P}[Z_d = k | V_{k,t}, d] \mathbb{P}[Z_d = k | \lambda_{ikt}]}{\sum_{q=1}^K \mathbb{P}[Z_d = q | V_{q,t}, d] \mathbb{P}[Z_d = q | \lambda_{iqt}]}. \quad (10)$$

To reduce computation, we approximate $\mathbb{P}[Z_d = k | \lambda_{ikt}]$ by $\lambda_{ikt} / \sum_{j=1}^K \lambda_{ijt}$, which can be interpreted as the average proportion of posts generated by node i assigned to topic k at time point t .

The topic assignment of a post can now be Gibbs sampled using equation (10). The sampler assigns the first post to a single topic, updates the topic-token distributions with the content of that post, then continues to the next post, and repeats. At each time point, the sampler sweeps

through the set of posts several times so that the topic assignments can stabilize. The ideal number of sweeps depends on the complexity of the posts on that day, but it need not be large. After some exploration, this study used 10 sweeps at each time point per iteration.

3.2 Node Specific Parameters

Once documents are assigned to topics, the next step is to update the node parameters, specifically the blog topic interest vector π_i and the blog posting rate ρ_i . The topic interest vector is updated in a Metropolis-Hastings step, where the proposal is a draw from a Dirichlet distribution with $\alpha = \pi_i |D_i|$, where $|D_i|$ is the total number of documents generated by node i . The likelihood is

$$\prod_{j=1}^T P(Z_{D_i} | \lambda_{it}), \quad (11)$$

which is the product of the Poisson probabilities for the current topic assignments of posts by blogsite i . A hierarchical prior is used, which is $\text{Dirichlet}(\alpha_{B_i})$, where the parameters are defined by the current block assignment of node i , as in equation (1).

The i th blog's posting rate ρ_i is also updated using a Metropolis-Hastings step, where the proposal distribution is a Normal truncated at 0, with mean equal to ρ_i and standard deviation equal to σ_ρ^2 . The likelihood evaluated is the same as in equation (11). The prior is a univariate Normal truncated at 0 and with mean ρ and variance σ_ρ^2 . Truncated normal distributions are used to uncouple the mean and the variance.

The activation matrix E is updated with a series of Metropolis steps for each time point and topic. The proposal is simply 1 if $E_{k,t} = 0$ and 0 if $E_{k,t} = 1$. The likelihood is still that in (11), and the prior is simply a Bernoulli with parameter E_π .

The activation parameters ψ_k are updated with Metropolis-Hastings steps, where the proposal is a truncated normal at 0 with mean ψ_k and standard deviation σ_ψ . The likelihood is similar to (11), but with the additional product over time. The prior distribution on ψ_k is a normal truncated at 0 with mean ψ and standard deviation σ_ψ^* .

3.3 Network Parameters

The network parameter set consists of the vector $\theta = (\theta_0, \dots, \theta_4,)$ as defined in equation (6). Each network parameter can be sampled using a Metropolis within Gibbs step. Specifically, the likelihood to be evaluated in this article is

$$\prod_{i \neq j} \prod_{t \in \{1, \dots, T\}} \frac{\exp((\theta_0 + \theta_1 B(i, j) + \theta_2 L_{jt} + \theta_3 I_j + \theta_4 O_i)^{A_{ijt}})}{1 + \exp(\theta_0 + \theta_1 B(i, j) + \theta_2 L_{jt} + \theta_3 I_j + \theta_4 O_i)}. \quad (12)$$

To update each parameter, one conditions on all other pieces of information in the model. Proposals are normal with mean set to the current value of the parameter, and a standard deviation specific to the parameter, while the priors are normal with a given mean and standard deviation.

3.4 Block Assignment

We describe a procedure for an unconstrained block structure, and then indicate simplifications to make estimation tractable. Let \mathcal{B} be the set of all possible combinations of K topics. For any reasonable K , the size of \mathcal{B} exceeds the number of blogs to assign to blocks. So the block assignment sampler must be able to account for blocks that have no members. This is a desirable property

since the analyst need not specify exactly how many blocks are in the model, unlike stochastic block models [14].

Block assignment for a given node i is informed by several pieces of data. The first is the position of node i within the network. The second are the topics in which node i is interested. One assumption of our model is that a node’s network position and topic interest are conditionally independent given block assignment, which in turn makes the sampling of a block assignment considerably simpler. Furthermore, a node’s potential block assignment must be informed by the number of nodes already assigned to the block, and if that block has any members at the current point in the MCMC chain. The probability that a node i will be assigned to the b th block is proportional to:

$$\mathbb{P}[B_i = b \mid A, \theta, \pi_i, B_{-i}] \propto \frac{N_{b,-i} + \alpha_B}{\alpha_B |B| + N - 1} P(A \mid \theta, B_i = b) P(\pi_i \mid B_i = b) P(|B| \mid \lambda_B)$$

where $N_{b,-i}$ is the number of nodes assigned to block b , not including node i , α_B is related to the prior probability of being assigned to any block (analogously to α in the topic model), θ is the complete set of network parameters, $|B|$ is the number of blocks with non-zero membership while node i is being considered for potential assignment to block b , and λ_B is the prior number of blocks expected to exist. Therefore $P(|B| \mid \lambda_B)$ is the Poisson probability of $|B|$ given λ_B .

For Gibbs sampling of the block assignment, this can be normalized with the sum of the probabilities over all blocks. However, it is computationally expensive to compute the probabilities of each possible block assignment without some sort of bound on the number of blocks, or on the blocks considered for node i ’s assignment. One way to reduce the number of blocks is to limit the number of topics in which a block is interested. In our work, blocks may be interested in at most three topics, except for one block that is interested in all topics (to account for such blogsites as *The Huffington Post* or *The New York Times*’s blogsite). Furthermore, during sampling, we restrict the blocks considered for a given node i by only considering blocks that have topics for which node i generated at least one post. These restrictions change the normalizing constant, though the relative probabilities of the blocks considered remains the same.

4 Political Blogs of 2012

We now analyze the top 467 US political blogs for the year 2012, as ranked by **Technorati**. This dataset has a dynamic network structure since blog posts often link to each other, responding to each other’s comments. Additionally, the topic structure of the blog posts reflect different interests, such as the presidential campaign or sensational crime. These topic vocabularies change over time, sometimes quite suddenly, as with the appearance of the tokens “Trayvon” and “Zimmerman” in March, 2012, and sometimes more gradually, as with the slow fade of the token “Gingrich” during the spring. Over the 366 days in 2012, the 467 political blogs generated 109,055 posts.

4.1 Data Preparation

The data used in this study were obtained through a joint research collaboration with MaxPoint Interactive, a company headquartered in the Research Triangle that specializes in computational advertising. Using the list of 467 U.S. political blog sites curated by **Technorati**, computer scientists at MaxPoint scraped all the text and links at those sites (after declaring robot status and following all robot protocols).

The scraped text was stemmed, using a modified version of Snowball [23] developed in-house at MaxPoint Interactive. The initial application removed all three-letter words, which was undesirable, since such acronyms as DOT, EPA and NSA are important. That problem was fixed and the data were restemmed.

The second step was filtering. This filtering was based on the variance of the unweighted term-frequency, inverse document frequency (TF-IDF) scores [24]. The TF-IDF score for token w in document d is

$$\text{TF-IDF}_{wd} = f_{wd}/n_w \quad (13)$$

where f_{wd} is the number of times that token w occurs in document d , and n_w is the number of documents in the corpus that use token w . Words that have low variance TF-IDF scores are such words as “therefore” and “because,” which are common in all documents. High-variance scores are words that are used often in a small number of documents, but rarely in other documents, such as “homosexual” or “Zimmerman”. Interestingly, “Obama” is a low-variance TF-IDF token, since it arises in nearly all political blog posts.

Next, we removed tokens that were mentioned in less than 0.02% of the total number of documents. This reduced the number of unique tokens that appeared in the corpus, as these were unlikely to be helpful in determining the topic distribution across all documents. Many of these were misspellings; e.g., “Merkle” for “Merkel”, the Chancellor of Germany.

After all tokens were filtered, we computed the n -grams, starting with bigrams. A bigram is a pair of words that appear together more often than chance, and thus correspond to a meaningful phrase. For example, the words “white” and “house” appear in the blog corpus often, in many different contexts (e.g., race relations and the House of Representatives). But the phrase “White House” refers to the official residence of the president, and appears more often than one would predict under an independence model for which the expected number of phrase occurrences is $Np_{\text{white}}p_{\text{house}}$, where N is the total amount of text in the corpus and p_{white} and p_{house} are the proportions of the text that are stemmed to “white” and “house”. Bigrams were rejected if their significance probability was greater than 0.05. In examining the bigram set generated from this procedure, it appeared to be too liberal; English usage includes many phrases, and about 70% of tested bigrams were retained. Therefore we excluded all bigrams with a frequency less than 500. This significantly reduced the set of bigrams.

After the bigrams were computed and the text reformatted to combine them, the bigramming procedure was repeated. This produced in a set of candidate trigrams (consisting of a previously identified bigram and a unigram), as well as a set of candidate quadrigrams (made up of two previously accepted bigrams). These candidates were retained only if they had a frequency greater than 100. This cut-off removed the majority of the candidate trigrams and quadrigrams. The final vocabulary consisted of 7987 tokens.

It is possible to go further, finding longer n -grams, but we did not. However, we identified and removed some long n -gram pathologies, such as the one created by a blogger who finished every post by quoting the Second Amendment. There is a large literature on various n -gramming strategies [25]. Our work did not employ sophisticated methods, such as those that use information about parts of speech.

4.2 Technical Details

Changes in the topics for this dataset are expected to be slow, aside from sudden events that abruptly add new tokens (e.g., “Benghazi” or “Sandy Hook”). Therefore, we used a lag parameter of 62 days to capture drift in the topics over time. Specifically, the distributions over the tokens

for each topic was estimated based upon a sliding window for the preceding 62 days. Within that window, all documents had equal weight.

To determine the number of topics, we used the criterion developed by [22]; there are several alternative criteria, but this one is principled and easy to compute. Figure 1 shows the criterion curve, which considers fitting anywhere between 1 and 30 topics. The curve has its minimum at 22, and thus our study fixes the number of topics to be 22.

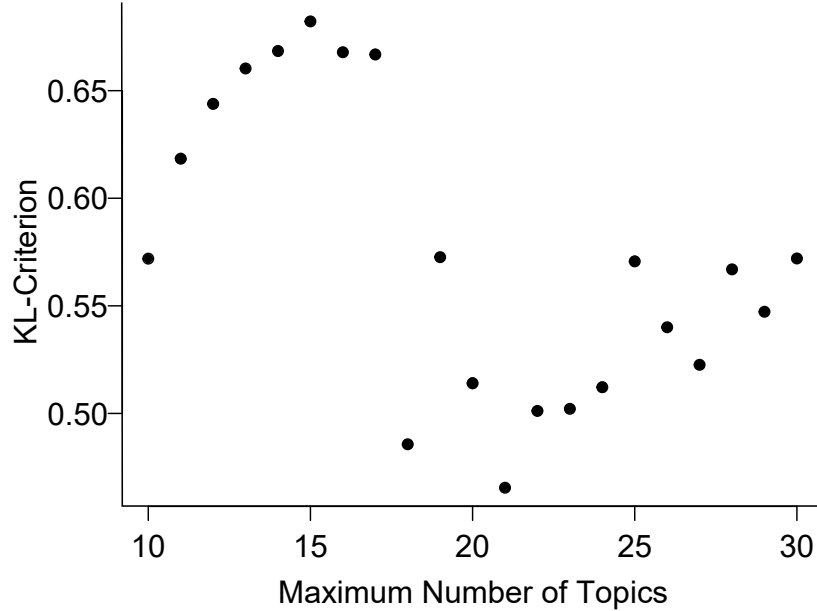


Figure 1: The criterion curve, as in [22], for determining the number of topics.

Once the number of topics is established, the restrictions on the blocks and the parameter P , as introduced in equation (1), can be set. Recall that each block may only be interested in 1, 2, 3 or all topics. And P was set to 50, to allow some freedom for blogs to post on topics outside of their block’s interests, but nonetheless mostly focus on the block’s interests.

The network model specified an edge parameter, a mean in-degree and out-degree parameter, a 7-day lag parameter, and a block membership parameter. The edge parameter acts as the intercept for the network model. Mean in-degree and out-degree are nodal covariates consisting of the average daily in-degree and out-degree for each node. This allows modeling of differentially popular blogs. Finally, to add in temporal dependency, the 7-day lag is an indicator function that takes the value 1 if and only if the pair of blogs has been linked within the previous 7 days, and is otherwise 0 (this captures the fact that bloggers sometimes have debates, which produce a series of links over a relatively short period of time). Vague priors were set for each of the network model parameters; all were normals with mean 0 and standard deviation 1000. The proposal standard deviation was set to 1 for the edge parameter, and to 0.25 for each of the other parameters in the network model.

For the topic model the α and β parameters were both set to 0.1. The prior for the average post rates ρ_i in equation (2) was a truncated normal at 0, with mean 4 and standard deviation 1000. The prior for topic activation parameters ψ_k in equation (2) was set as a truncated normal

at 0 with mean 0 and standard deviation 1000, and a proposal standard deviation of 0.5.

Additionally, 25 was set as the prior mean number of blocks (λ_B), and the prior tendency for block membership α_B was set to 1. The prior probability of topic activation was set to 0.2.

The sampler ran for 1000 iterations. To ensure mixing for the network parameters, at each iteration the network parameters were updated 10 times. During each iteration, there were 10 sub-iterations for the topic model and 10 sub-iterations for the block assignments. The first 100 overall iterations were discarded as burn-in, the remaining 900 were thinned at intervals of 10.

4.3 Results

The sampler converged to stationarity quickly in every parameter. To assess the mixing of the post to topic assignment, and of the blogger to block assignment, we calculated Adjusted Rand Indices [26, 27] for each iteration i compared to iteration $i - 1$. The document to topic assignment was very stable, with a mean Adjusted Rand Index of 0.806 and standard deviation 0.047. The block assignment was less stable, with a mean Adjusted Rand Index of 0.471 and standard deviation 0.031. We believe this variability is due to the fact that many bloggers tended to post on whatever news event captured their attention, making it difficult to assign them to a block with interest in no more than three topics. However, their interests were not so wide that they were reasonably assigned to the block that is interested in all topics.

All domain level parameters converged successfully. The domain rate parameter ρ_i was estimated for each domain, and the posterior means of the domain rates had a mean of 0.632 and a standard deviation of 1.67. The largest domain rate was 22.69. The distribution of domain post rates was highly skewed, with few blogs having a very high average post rate, and most blogs having a lower post rate.

The topic specific activation parameters ψ_k converged successfully. Information on the posterior means and standard deviations is in Table 3, and were calculated after the topics had been defined. The topics Election and Republican Primary have the greatest posterior means, which suggests that these topics were more event driven than other topics.

4.3.1 Topic Results

The topic model found 22 topics, each of which had distinct subject matter. Table 1 contains the topic titles and total number of documents in each topic, as well as the three tokens that have the highest predictive probability for that topic over all days. Predictive probability was calculated using Bayes' rule:

$$P(Z_d = k | w \in d) = \frac{P(w \in d | Z_d = k)P(Z_d = k)}{P(w \in d)}. \quad (14)$$

Table 2 contains the five most frequent tokens in each topic over all days. Topics were named by the authors on the basis of the most predictive tokens as well as the most frequent tokens over all days. Some of these tokens may seem obscure, but in fact they are generally quite pertinent to the identified topics.

Table 1: Topic names and their most specific tokens.

Topic Name	# of posts	Highest Specificity Tokens		
		1	2	3
Feminism	3971	russel.saunders.juli	circumcis	femin
Keystone Pipeline	4422	loan.guarante.program	product.tax.credit	tar.sand.pipelin
Birth Control	2703	contracept.coverag	birth.control.coverag	religi.organ
Election	14713	sopic	cherokee	eastwood
Mortgages	2130	estat	probat	fiduciari
Entertainment	10555	email.read.add	olivia	free.van
Middle East	6068	mursi	morsi	fatah
LGBT Rights	5425	anti.gay.right	support.equal.marriag	equal.marriag
Sensational Crime	6423	zimmerman	lanza	mass.shoot
Technology	3230	mail.feel.free	pipa	ret
Supreme Court	1767	commmerc.claus	bork	chief.justic.robert
Bank Regulation	5222	volcker	dimon	libor
National Defense	1977	iaea	iranian.nuclear.weapon	warhead
Republican Primary	9351	poll.mitt.romney	nation.popular.vote	romney.lead
Voting Laws	7865	ohio.secretari.state	voter.registr.form	hust
Political Theory	1448	bylaw	rawl	sweatshop
Eurozone	1832	standalon	troika	ecb
Taxation	8435	tax.polici.center	health.care.spend	top.tax.rate
Diet and Nutrition	3057	spielberg	harlan	calori
Education	2909	chicago.teacher.union	chicago.public.school	charter.school
Global Warming	2205	arctic.sea.ice	sea.ice	sea.level.rise
Terrorism	3347	kimberlin	broadwel	assang

Table 2: The most frequent words in each topic.

Topic Names	Most Frequent Words				
	1	2	3	4	5
Feminism	women	peopl	dont	person	life
Keystone Pipeline	energi	oil	price	compani	industri
Birth Control	right	state	law	marriag	women
Election	obama	romney	peopl	presid	polit
Mortgages	case	court	bank	judg	attorney
Entertainment	peopl	dont	good	work	game
Middle East	israel	islam	american	peopl	countri
LGBT Rights	gay	peopl	marriag	homosexu	support
Sensational Crime	gun	polic	report	peopl	zimmerman
Technology	compani	googl	facebook	appl	user
Supreme Court	law	court	state	case	constitut
Bank Regulation	bank	market	money	price	compani
National Defense	iran	militari	israel	nuclear	obama
Republican Primary	romney	republican	obama	poll	vote
Voting Laws	state	vote	elect	voter	counti
Political Theory	libertarian	peopl	right	state	govern
Eurozone	bank	debt	economi	rate	govern
Taxation	tax	state	govern	cut	obama
Diet and Nutrition	peopl	dont	govern	polit	work
Education	school	student	teacher	educ	state
Global Warming	climat	climat.chang	temperatur	scienc	scientist
Terrorism	report	govern	attack	inform	case

Table 3: Topic Specific Activation Parameters ψ_k

Topic	Posterior Mean	Standard Deviation
Feminism	0.0034	0.0029
Keystone Pipeline	0.0037	0.0017
Birth Control	.00001	.00003
Election	0.3917	0.0249
Mortgages	.00001	.00005
Entertainment	0.0018	0.0014
Middle East	0.0378	0.0129
LGBT Rights	0.0028	0.0026
Sensational Crime	0.0208	0.0085
Technology	0.0012	0.001
Supreme Court	0.0022	0.0032
Bank Regulation	0.0021	0.0021
National Defense	0.0014	0.0013
Republican Primary	0.2267	0.0188
Voting Laws	0.0375	0.0095
Political Theory	0.0012	.00001
Eurozone	0.0001	.00002
Taxation	0.0135	0.0084
Diet and Nutrition	0.0804	0.0139
Education	0.0011	0.0012
Global Warming	0.0019	0.0011
Terrorism	0.0022	0.0019

It is beyond our scope to detail the dynamics of all 22 topics. But a close look on one topic, Sensational Crime, shows the kind of information this analysis obtains. The posts about Sensational Crime largely concerned four events: the shooting of Trayvon Martin in February, the Aurora movie theater massacre in July, the Sikh Temple shooting in August, and the Sandy Hook massacre in December.

To illustrate how the salience of a token changes over time, we use a weighted frequency proportion which is equal to:

$$WF_{w \in k} = \frac{P(Z_{d_t} = k_t | w \in d)F(w \in k_t)}{\sum_{w^* \in V} P(Z_{d_t} = k_t | w^* \in d)F(w^* \in k_t)} \quad (15)$$

where $F(w \in k_t)$ is the frequency of the token w in the k th topic’s token distribution at time t . This weighted frequency can be interpreted as the proportion of topic specific tokens at time t that is taken up by token w , and is useful in this context as many of the tokens are shared at high frequency between topics (such as ”people”) and are therefore uninformative. So this quantity tracks the topic specific information of a token over time. Recall that the topic word distributions are computed over the past 62 days, which accounts for the smoothness of the curves. The gray shading around each curve represents the 95% Bayesian credible interval.

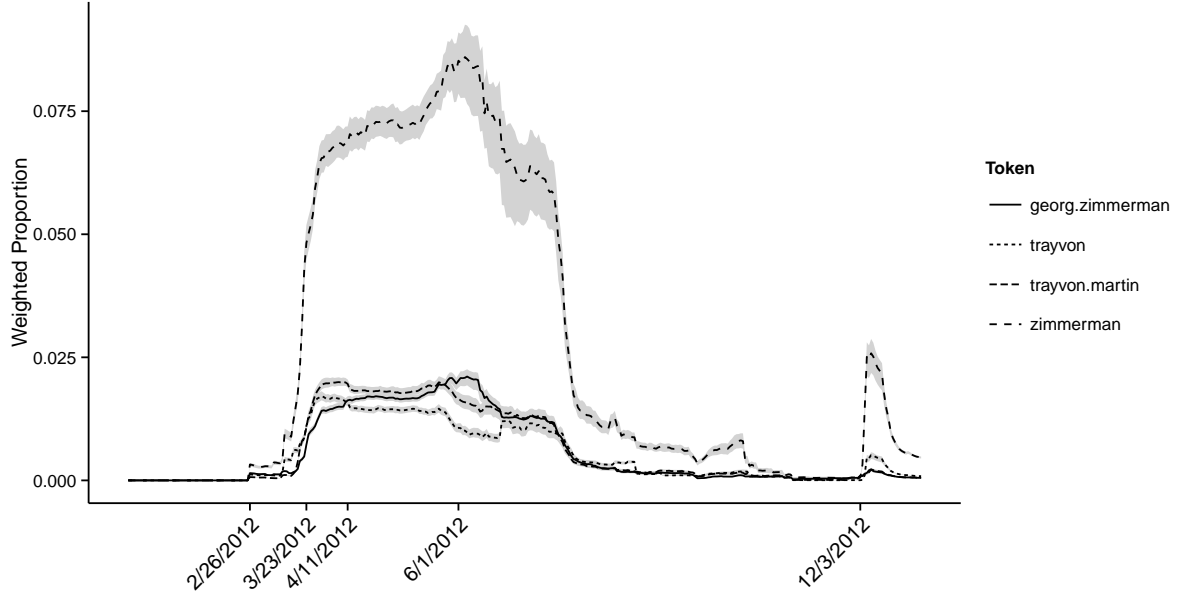


Figure 2: Weighted proportion timeline of the Trayvon Martin shooting and the subsequent legal case. The date 2/26/2012 is when Trayvon Martin was shot, 3/23/2012 is when President Obama said that Trayvon could have been his son, 6/1/2012 was when Zimmerman’s bond was revoked, and 12/3/2012 was when photos were released showing Zimmerman’s injuries on the night of the shooting. (95% credible intervals shown.)

Figure 2 presents the weighted frequency curves for tokens specifically related to the shooting of Trayvon Martin. The plot shows three interesting features. First, the prevalence of all of the tokens does not spike up at the time of the shooting (2/26/2012), but rather at the time of Obama’s press statement regarding the shooting. Second, the term “zimmerman” dominates the tokens, and in fact is the most prevalent token in the whole of the Sensational Crime topic from March 22 to July 16th. The gap in prevalence between the tokens of “zimmerman” and “trayvon” or “trayvon martin” is also interesting, suggesting that in this case, media attention was on the perpetrator rather than the victim.

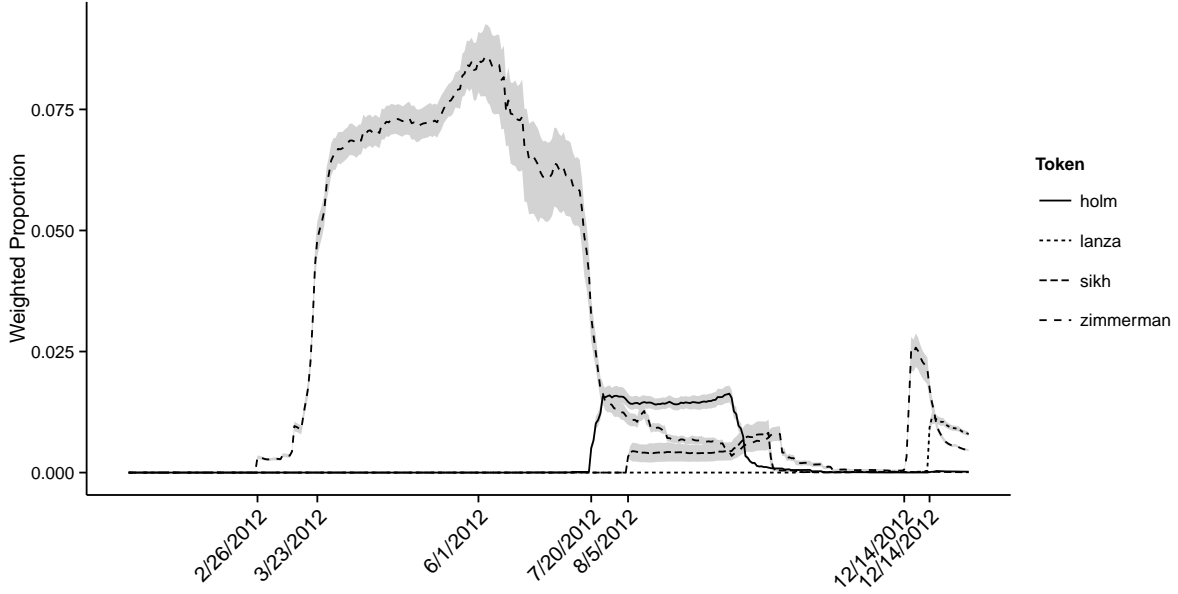


Figure 3: Weighted proportion timeline of major events in the Sensational Crime topic. The date 2/26/2012 is when Trayvon Martin was shot, 3/23/2012 is when President Obama says that Trayvon could have been his son, 6/1/2012 is when Zimmerman’s bond was revoked, 7/20/2012 is the Aurora mass shooting by James Holmes, 8/5/2012 is the Sikh Temple shooting by Michael Page, 12/3/2012 is when photos showing Zimmerman’s physical injuries were released, and 12/14/2012 is when the Sandy Hook massacre occurred. (95% credible intervals shown.)

Figure 3 tracks the major events in the Sensational Crime topic for the entire year. Notably, media focus is never as strong on the tokens related to the events as it is on “Zimmerman” specifically. Rather, the usual top terms over the course of the year are “police” and “gun”. Also notable is the lack of events in the later part of the year after the media attention on the Sikh Temple Shooting receded.

4.4 The Network Results

The use of network data improves the topic discovery, based on a comparison to analysis of the same dataset by [28] that used only the text. However, this analysis also enables us to use the topic modeling to improve community detection, through the incorporation of the interest-group block structure.

Table 4 shows the posterior means of the network parameters with 95% credible intervals. The edge parameter posterior mean indicates that the network is rather sparse at most time points. Interestingly, the 7-day lag parameter was negative, suggesting that blogs which were recently linked were less likely to link in the near future. There are two plausible explanations for this finding. First, the linkage dynamics may not be driven by recent links, but rather the links are a consequence of the events taking place. An upsurge in linking when an event occurs is followed by a decrease in the number of links as the event fades out of the news cycle. Second, if linking is done as part of a debate, then once a point has been made, the bloggers may not feel a need for back-and-forth argument.

The block parameter is strongly positive (mean = 1.058, standard deviation 0.240), suggesting

that blogs which share common interests are more likely to link to each other. This is particularly important, as the block statistic was not only formed from explicit block matching, but also from blogs that did not share the same interests. The block statistic is proportional to the shared topic interests. This result directly links the network model to the topic model, and allows the analyst to make claims about the block structure as inferred from the topics.

Finally, and predictably, both the in-degree and out-degree of a blog increases the probability that the block will receive links. These parameters were included in the analysis to control for the influence of highly popular blogs such as *The Blaze* and *The Huffington Post*.

Table 4: Posterior means and 95% credible intervals for network parameters.

Parameter	Posterior Mean	95% CI
Edges	-8.524	[-8.539, -8.513]
7 day lag	-0.163	[-0.198, -0.131]
Block	1.058	[0.638, 1.485]
Outdegree of Receiver	0.330	[0.329, 0.332]
Indegree of Receiver	0.497	[0.496, 0.499]

We can examine the link dynamics within a topic block. There were 21 blogs whose maximum posterior probability of block assignment placed them in the block that was only interested in the Sensational Crime topic. Only 2 of these 21 blogs received any links over the course of the year, and only 1 received links within the block (*legalinsurrection.com*). While this runs counter to the idea that they form one block, recall that blogs are also more likely to link to blogs that share some of the same topic interest. There are a total of 62 blogs to which members of the Sensational Crime block link, and 15 of these blogs receive approximately 90% of the links. As such, the Sensational Crime topic block appears to be a set of “commenter” blogs that react to posts that are posted on larger blogs. Our model allows the analyst to isolate the blogs that post on a particular topic, to get a better idea of the linkage dynamics around important events. As an example, we describe how the linkage pattern changes around the occurrence of Barack Obama’s speech regarding the shooting of Trayvon Martin, and also following the Aurora shooting.

Figures 4 and 5 show the link structure from the blogs in the Sensational Crime block to other blogs. The data are aggregated over fifteen days. Figure 4 pertains to the days before President Obama’s press conference regarding Trayvon Martin on 3/23/2013, and Fig. 5 pertains the days following his remarks. Figure 6 pertains to the period immediately before the Aurora shooting on 7/20/2012, and Fig. 7 pertains to the period immediately after.

To improve interpretability, only a subset of blogs and links are plotted. Specifically, blogs that were assigned to the block interested only in Sensational Crime, and who posted during the specified time frame, are plotted. Additionally, blogs who are part of the 15 blog subset that received 90% of the links from the Sensational Crime block, and which received links within the timeframe, are plotted. Also, links generated from blogs in the Sensational Crime block to other members of the same block, or to other blogs, are plotted. Links emanating from the 15-node subset are not plotted. These plotting constraints help enable us to discern and interpret the community structure that formed in the discussion of these events.

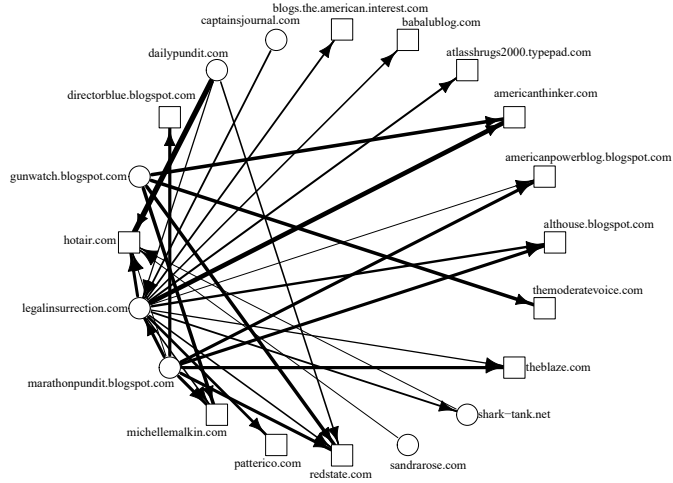


Figure 4: Fifteen day aggregate linkage from 3/8/2012 to 3/22/2012, immediately before President Obama's comment. The number of links, represented by line thickness, is root transformed for clarity. Circular nodes are blogs in the Sensational Crime block. Square nodes are blogs to which the Sensational Crime blogs link, and these blogs are generally in multi-topic blocks, where one of the topics is Sensational Crime.

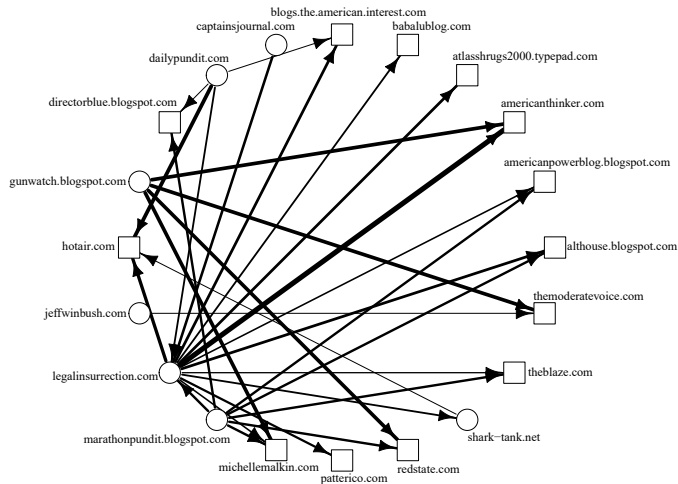


Figure 5: This figure is constructed in the same way as Fig. 4, but for the time period from 3/23/2012 to 4/6/2012, immediately after President Obama's comment.

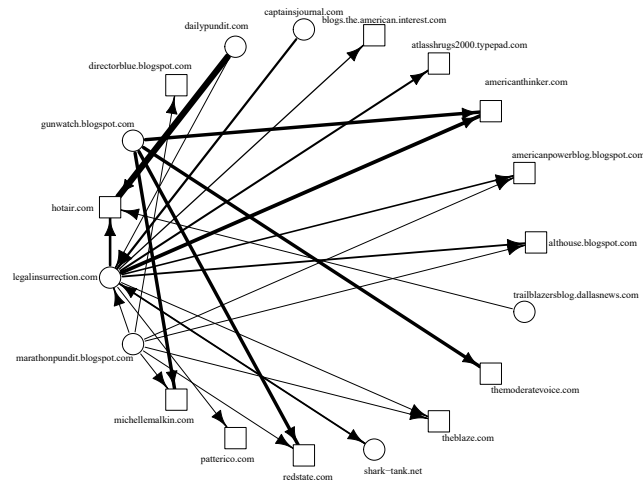


Figure 6: This figure is constructed in the same way as Fig. 4, but for the time period from 7/5/2012 to 7/19/2012, immediately before the Aurora shooting.

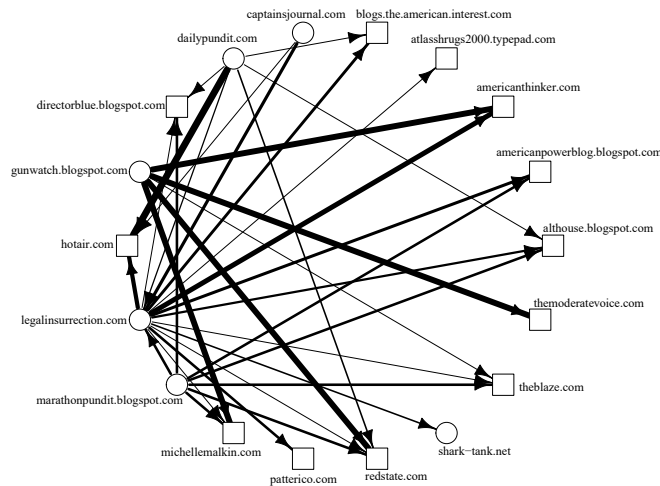


Figure 7: This figure is constructed in the same way as Fig. 4, but for the time period from 7/20/2012 to 8/2/2012, immediately after the Aurora shooting.

Comparing Figs. 4 and 5 shows that the community structure seen in the linkage pattern did not change much as a result of the press conference in which President Obama remarked that if he had a son, he would resemble Trayvon Martin. Remarkably, there was also no net increase in

posting rates. It is known that there was a flurry of posts at this time, and it turns out that uptick was allocated to the Election block, as people speculated on how his remarks would affect the 2012 presidential election.

The patterns surrounding the Aurora shooting (Figs. refA1 and 7) are more clear. The community structure in the discussion is essentially the same, but the amount of traffic increases conspicuously. Specifically, the number of links in the 15 days before the shooting was 197, but afterwards it was 427. Linkage rates especially increase from `gunwatch.blogspot.com`. In general, this agrees with the conclusion that the methodology is able to detect stable communities whose linkage rates are driven by news events.

To further illustrate the findings of the network model for a different block, we now present examples from the Election block. There are 52 blogs that the model assigned to the block whose only interest was the presidential election. Of these 52 blogs, 33 blogs linked to or received links from other blogs within this same block. And of these 33 blogs, 12 were the recipients of all links. We use random walk community detection [29] upon the Election block to show that the model can extract meaningful subnetworks for use in secondary analyses.

Figure 8 shows the community substructure for the Election block aggregated over the entire year. Random walk community detection indicates that seven communities optimized modularity, but two communities contained the majority of the blogs. As such, for interpretability, only these two communities are shown. The modularity of this partition is 0.49, and a 10,000 sample permutation test of the community labels indicated that this value of modularity was in the 99th percentile (the greatest modularity found in the permutation test was 0.317). This result indicates that the model found meaningful community structure, rather than sampling variability.

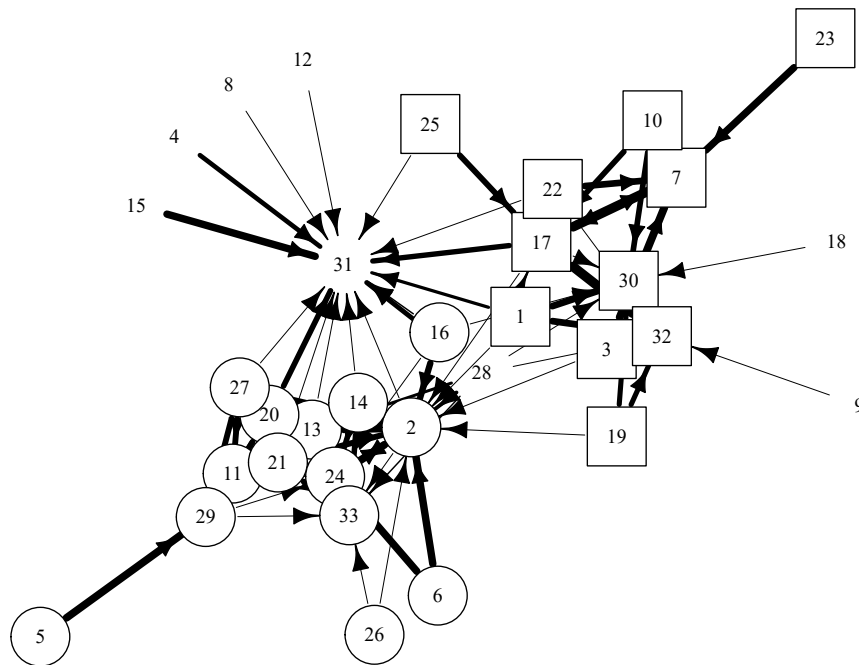


Figure 8: Community substructure of the Election block. Circles and squares denote separate communities. The absence of shape denotes membership in a small community. The thickness of edges correspond to a log transformation of the number of links sent over the entire year.

Table 5 contains the blog labels for the Election block network. Examination of the block

structure shows that the majority of the blogs partitioned into one of two communities. Based on **Technorati** ratings, the community plotted as circles in Figure 8 is politically conservative, while the other community plotted as squares is liberal. This separation of the two ends of the political spectrum has been found before in blogs [30]. There is little communication between the two communities, but a lot of communication within those communities. Interestingly, both communities sent many links to blog 31, which was allocated into a distinct community that it shared with blogs 15, 4 and 28. Blog 31 is *mediaite.com*, a non-partisan general news and media blog, and the pattern of links from both partisan communities suggests that *mediaite.com* acts as a common source of information.

Table 5: Blog names and their community membership.

Label	Blog	Community
1	afeatheradrift.wordpress.com	1
2	atlasshrugs2000.typepad.com	3
3	bleedingheartlibertarians.com	1
4	brainsandeggs.blogspot.com	2
5	citizentom.com	3
6	crethiplethi.com	3
7	crookedtimber.org	1
8	davedubya.com	4
9	dogwalkmusings.blogspot.com	5
10	driftglass.blogspot.com	1
11	greatsatansgirlfriend.blogspot.com	3
12	hennessysview.com	6
13	joshuapundit.blogspot.com	3
14	marezilla.com	3
15	mediabistro.com	2
16	michellesmirror.com	3
17	nomoremister.blogspot.com	1
18	ochairball.blogspot.com	7
19	patriotboy.blogspot.com	1
20	righttruth.typepad.com	3
21	rightwingnews.com	3
22	rogerailes.blogspot.com	1
23	rwcg.wordpress.com	1
24	sultanknish.blogspot.com	3
25	tbogg.firedoglake.com	1
26	thecitysquare.blogspot.com	3
27	therightplanet.com	3
28	thoughtsandrantings.com	2
29	varight.com	3
30	blogs.suntimes.com	1
31	mediaite.com	2
32	rightwingwatch.org	1
33	patdollard.com	3

5 Conclusion

In this manuscript we present a novel Bayesian model for analyzing dynamic text networks. This model links the network dynamics to topic dynamics through a block structure that informs both the topic assignment of a document and the linkage pattern of the network. One advantage is

the flexibility of the network model. A second advantage is that the block structure enables interpretable associations among topics. For example, there is a two-topic block whose members are interested in both Election topic and the Republican Primary topic, but there is no block whose members are interested in just the Supreme Court and Global Warming. That pattern of shared interest conforms to what one would expect.

This analysis uses a limited set of predictors, but the ERGM modeling framework can easily incorporate additional covariates [31] and structural features. Additionally, if one uses a maximum pseudo-likelihood approach [17] as a way of approximating the likelihood, then higher order subgraph terms, such as number of triangles or geometrically weighted edgewise shared partners [32] can account for transitivity effects. Finally, while the block structure modeled in this paper was based upon similarity in topic interest, more nuanced models are possible, and these could use information on, say, political ideology, which the analysis of the Election block found to be important in predicting linkage patterns.

Another strength of our approach is the nonparametric nature of the topic dynamics. By avoiding an autoregressive specification of topic dynamics, as in [4], topics are able to change more freely; in particular, it is possible for new tokens with high probability to emerge overnight. This is ideal for the blog data, since the bloggers are often responding to news events.

We demonstrated the utility of our approach on a political blog dataset spanning the year of 2012. This dataset had an interpretable topic and block set, and analysis of the Sensational Crime block and the Election block reached reasonable conclusions. Specifically, the dominance of the token “zimmerman” across the year agrees with our sense of the tone and primacy of that discussion, and the spike following the Aurora shooting is commensurate with its news coverage. And the Election block neatly split into subcommunities along partisan lines, which accords with previous research [30].

Finally, the focus in this manuscript was the methodological development, but there are many political science questions that await deeper exploration. Among these are study of the matrix that models topic activation, which can be linked to specific headline events, the use of political affiliation as a covariate in the linkage dynamics, and examination of the association structure among blocks that are interested in more than one topic.

The methodology is generalizable to other dynamic text networks, such as the Wikipedia and scientific citation networks. However, each application requires some hand fitting that captures specific aspects of the data. For example, the block structure might need to be dynamic; this would make sense in scientific citation networks, since disciplines sometimes bifurcate (e.g., the computer science of 1970 has now split into machine learning, quantum computing, algorithms, and many other subfields). Also, scientific citation is strictly directional in time—one cannot cite future articles. But the Wikipedia is not directional in time; an article posted a year ago can send a link to one posted yesterday. So specific applications will require tinkering with the model described here.

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